

Visual analytics: tackling data related challenges in healthcare process mining

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Abstract

Data-science approaches such as Visual analytics tend to be process blind whereas process-science approaches such as process mining tend to be model-driven without considering the “evidence” hidden in the data. Use of either approach separately faces limitations in analysis of healthcare data. Visual analytics allows humans to exploit their perceptual and cognitive capabilities in processing data, while process mining represents the data in terms of activities and resources thereby giving a complete process picture. We use a literature survey of research that has deployed either or both Visual analytics and process mining in the healthcare environments to discover strengths that can help solve open problems and challenges in healthcare data when using process mining. We present a visual analytics (data science) approach in solving data challenges in healthcare process mining (process science). Historical data (event logs) obtained from organizational archives are used to generate accurate and evidence-based activity sequences that are manipulated and analysed to answer questions that could not be tackled by process mining. The approach can help hospital management and clinicians among others, audit their business processes in addition to providing important operational information. Other beneficiaries are those organizations interested in forensic information regarding individuals and groups of patients.

Keywords: Healthcare, visual analytics, process mining, challenges

Introduction

In some countries such as the Netherlands, it is a requirement that healthcare procedures be standardized and auditable (Helderman et al., 2005). Unlike in industry such as manufacturing, healthcare procedures are unique.

In healthcare, individual actors, say doctors, though initially trained to treat patients using specific procedures and drugs, the procedures and drugs are continuously changing; likewise individual patients may present non-standard symptoms or suffer complications. Interest in healthcare is beyond individual hospitals.

Organizations such as insurance companies, governments and even international organizations are interested in an efficient healthcare system. In the United States of

America, healthcare accounts for 17% of the GDP and employs 11% of the countries workers, yet its costs have been growing at 5% in the last decade making it unsustainable and a major contributor to the high national debt levels projected in the next two decades. One of the leading contributors to these situations is that little has been invested in healthcare efficiency optimization (Manyika et al. 2011).

Many authors including Mans, 2011, categorize healthcare processes into two: (1) Organizational/Administrative processes: - Include resources (staff, machines and equipment) and their scheduling. (2) Clinical/Medical Processes: -These constitute the decisions made by qualified clinicians on the treatment of a patient such as diagnosis, laboratory tests, imaging, prescriptions and drug administration, discharge and follow-up.

Clinical and Administrative processes in healthcare have high complexity due to the many decisions and procedures captured, are highly dynamic, increasingly multidisciplinary and ad hoc; hence cannot fit in a-priory model. The only accurate way to know what is happening is to mine the process model from historical data. On the other hand, optimization or improvement of a process model alone cannot improve the process due to dynamism of procedures and other factors.

Process mining is able to build a process from historical data that is accurate, and evidence based. It is good at *portraying processes that have many vertices (activities) and flow lines (edges)*. However, Process mining is unable to deal with complexity, resulting in unreadable process models and does not portly what is happening to individual records or even groups of record (Riemers, 2009).

Visual analytics is defined as “combining automated analysis techniques with interactive visualizations for an effective understanding, reasoning and decision making on the basis of very large and complex data sets” (Keim et al., 2010). Visual analytics is human-centered, whereby a human solves a complex problem with the help of a computer.

It is an important candidate for handling information overloads and complexity as well as being interactive (Keim et al. (2008). The disadvantage of Visual analytics is that it is process blind (e.g. event sequences do not show the relationship between different variants say sharing of resources, convergence of work, parallelism, et cetera). However, it is good at portraying the “evidence” hidden in the data e.g longest paths, variants, et cetera.

This paper aims to answer three out of four data challenges when answering frequently posed questions in healthcare process mining (Mans, 2013). They include:

RQ1: What are the most followed paths and what exceptional paths are followed?

RQ2: Are there differences in care paths followed by different patient groups?

RQ3: Do we comply with internal and external guidelines?

Related literature

A search of literature using the keywords visual analytics, process mining, healthcare and challenges resulted in four categories of reports including: (1) those that involve both visual

analytics and process mining, (2) visual analytics; (3) process mining and (4) other interesting findings.

Among those that employed both visual analytics and process mining is Riemers (2009) and Ramos (2009), the later being validation of the formers work. Riemers and Ramos did not address any of the three research questions but their work generally describes and recommends a combined approach of the two technologies that is also recommended widely in the visual analytics community.

A study by Gschwandtner (2017) lists a set of six open challenges in process mining four of which can be mapped on to the three research questions in this study. The challenge of combining the purely automatic analysis associated with process mining and visualization methods has been highlighted by a number of researchers (van der Aalst 2011, De Leoni et al., 2012; Monroe, 2014; Ozkaynak, et al., 2015).

Some research reports that deployed visual analytics and used electronic health records or log data don't describe the data extraction method (De Leoni et al., 2012; Monroe, 2014; Ozkaynak, et al., 2015). However they mention the need for a combined approach to problem solving as Monroe went ahead to develop Eventflow toolkit.

Other research that focused on healthcare used visual analytics and data mining instead of process mining (Perer & Gotz, 2013; Fitzgerald & Dadich, 2009). This approach also used by the IBM Watson research is based on data mining and is used to answer predetermined questions.

In a study to apply Process Mining in healthcare, Mans et al., (2008) used process mining without visual analytics. They however ended up recommending development of new techniques and or using existing techniques in an innovative way to obtain understandable high-level information instead of the spaghetti-like models showing all details.

A similar suggestion to handle abstraction and complexity using integration, visualization and interaction though not based on healthcare or the two technologies was made by Nugteren (2010). Visual analytics has capacity to handle Nugteren's suggestions on abstraction and complexity.

Research involving healthcare workflows that employed process mining without visual analytics identified one of the challenges to be the inability of process mining to portray one-to-many and many-to-many relationships between Proclots e.g. mini-processes (Mans, 2011), a challenge that can be handled by visual analytics to some extent.

The combination of visual data exploration (a data science approach) with process mining algorithms (a process science approach) makes complex information structures more comprehensible and facilitates new insights (Gschwandtner 2015). Data-science approaches tend to be process blind (e.g. event sequences do not show the relationship between different variants say sharing of resources, convergence of work etc) whereas process-science approaches tend to be model-driven without considering the "evidence" hidden in the data (e.g longest paths, variants, etc).

VA is good at handling abstraction and complexity in data, it is not ideal for portraying processes that have so many vertices (activities) and flow lines (edges). The implication is that data science may not be of much use in process issues such as control flow or dealing with concurrency but can support in issues to do with aggregation and abstraction and sequence.

Likewise process science may not be that efficient in abstraction aggregation or sequence issues but can help in showing the relationship between different data elements and activities. For example, process science can help show the control flow issues such as bottlenecks while data science can help analyze the data around it. Indeed VA can be used to answer some of the data challenges encountered in application of process mining in healthcare as posed in Mans et al (2013).

Obviously, both worlds need to be connected and integrated (Harmon et al. 2016). ProM an open source framework available from www.processmining.org and Eventflow toolkit developed by University of Maryland are among tools that are applicable to process mining and visual analytics respectively.

On the other hand, research on visual analytics also reports a number of challenges. Appropriate combination of the strengths of intelligent automatic data analysis with the visual perception and analysis capabilities of the human user has been recommended (Kohlhammer et al. (2011).

Kohlhammer further underscores the need for faster new solutions to highly complex problems, as targeted by visual analytics, through the promotion of interdisciplinary research. He also calls for use of incremental improvements to generate broader support in various application fields using visual analytics.

Typical data analysis using visual analysis involves search for known patterns from data and prediction of unexpected information remains a challenging problem (Hong et al (2015). Finally, there is need for integrative solutions for interactive visualization of the data.

Although there are many sophisticated results and paradigms from the visualization community, integrated solutions, e.g. within business hospital information systems, are rare today (Turkay et al., 2014). Most of the challenges highlighted with regard to visual analytics can be tackled by applying visual analytics to solving the three process mining data challenges by Mans (2013).

Method

To answer the research questions, we use event-log data from the Radiology department of the AMC University teaching hospital, a Dutch hospital of the Netherlands that is freely available at www.processmining.org.

The event-log was converted from XSS and saved as MXML for ProM and txt for Eventflow. Other departments were filtered out to obtain event-logs relating to radiotherapy department only. As with most hospital information systems a number of common issues were noted (Mans et al., 2013).

Some of the issues could be addressed yet others had no immediate solution as follows: (1) event-log has average abstraction e.g. one event referring to an individual task which is a positive factor. (2) accuracy of the data viewed in three sub dimensions was as follows: the data had average granularity (hours) with the resources are in block form e.g. RATH and SRTH; low directness of registration (timestamps are registered manually e.g. almost all end at 2:00 pm the next day); and low correctness (timestamps not logged correctly in the chosen granularity e.g. mixed date formats, some start times coming after the end time), duplication of records and single entries that do not constitute a procedure or trace in a process.

Apparently, such data challenges are a problem common in both VA and process mining (Gschwandtner, 2015). This could be attributed to the many actors, some who do not follow standard procedures, responsible for entering data into the systems that store such data.

Each event in the data had a CaseID, TaskID, Start timestamp, End timestamp, diagnosis Code and resource. The event-log had 329 cases consisting of 4322 events. Using Eventflow and the radiology event-log, the three research questions are answered as follows.

RQ1: What are the most followed paths and what exceptional paths are followed

a) Most followed path

The data that was earlier on saved as text is used as input to Eventflow. A raw event-log view of radiology department is generated representing all the information, some of which is unnecessary and too complex for the eye to pick out required information.

The activities of each record/case are represented taking into account the timestamps on the overview panel as shown in Figure 1. The timeline panel shows the same information in a format similar to a Gantt chart.

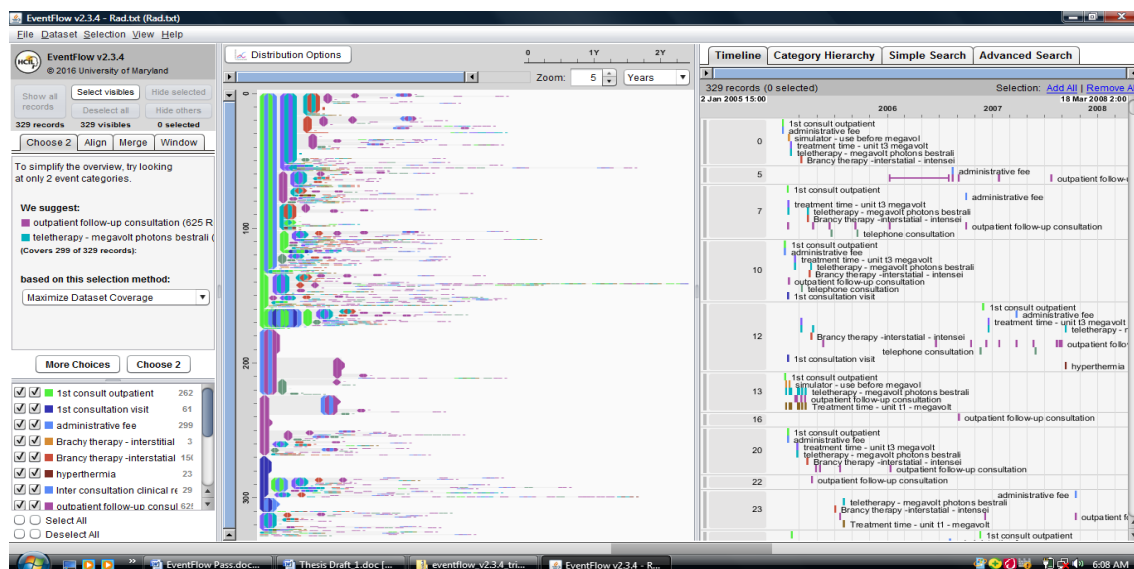


Figure 2: Un-optimized Radiology department showing all case activities

To reduce the complexity, administrative fee and outpatient follow-up consultation were checked off since they either don't constitute treatment or it is common to almost all patients at the end hence cannot help in discriminating between traces.

This reduces the overview complexity of the view, placing the most common sequence at the top as depicted in Figure 2. The overview panel is ranked based on number of records in ascending order.

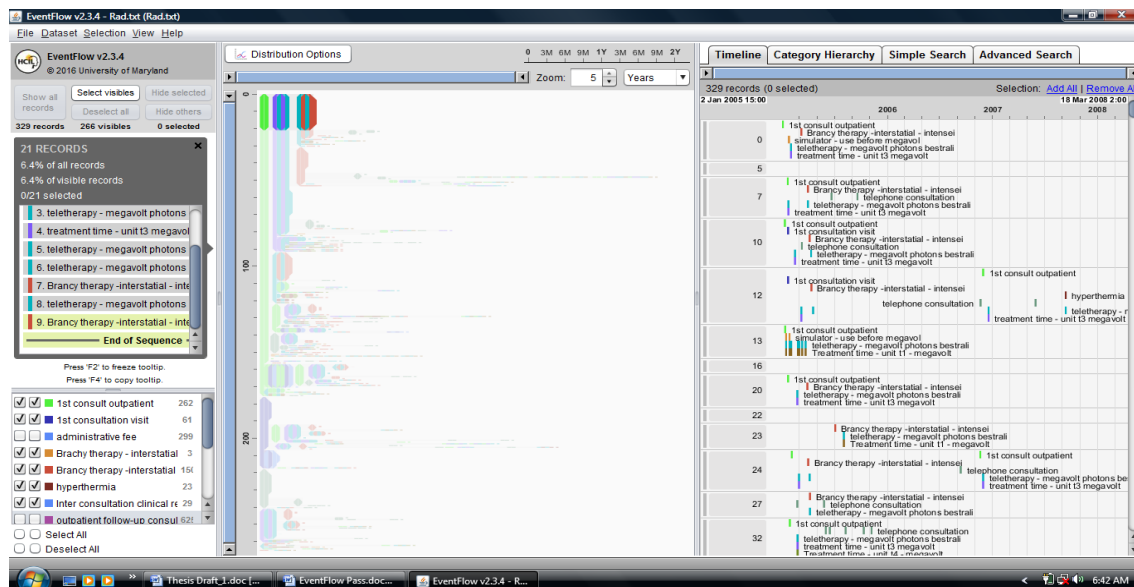


Figure 2: Most common sequence/trace in the radiology process

The events in the trace consist of: (1) 1st consultation outpatient, (2) treatment time unit t3 megavolt, (3) Teletherapy – megavolt photons bestrali and Branchy therapy – interstitial – intensi. On completion, the sequence/trace constitutes 6.4% of all records.

b) Exceptional paths

By checking off administrative fee which does not constitute treatment complexity is reduced. The view presents a number of mostly single records that are exceptionally long such as case number 536 that is highlighted with 70 events in figure 3. Others can consist of single events such as payment of administrative fee without any other service. Exceptional paths are usually of special interest to the process owners.

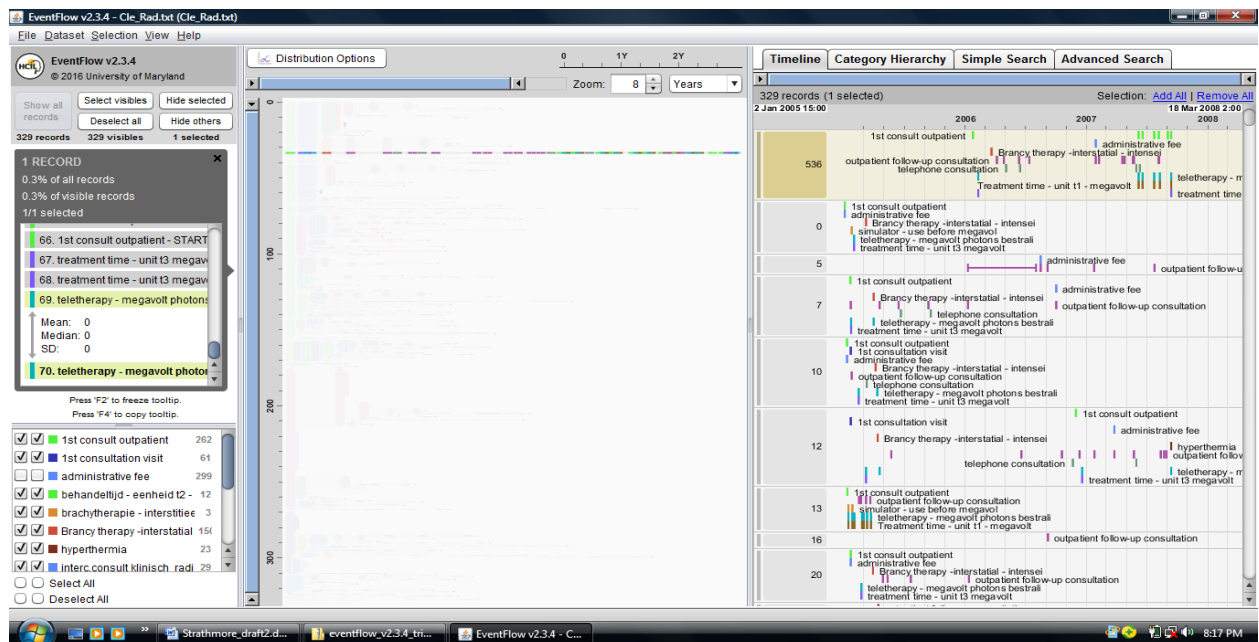


Figure 3: Exceptional Record number 536

RQ2: Different care paths followed by different patient groups

Different patient and groups often follow different care paths despite having the same diagnosis. To generate the view, consultation and administrative fee categories are checked off to reduce complexity since they are only used to determine diagnosis and payment rather than actual treatment.

Creation of such a view requires an attribute file that matches the cases with the specific diagnosis. All case are then grouped according to diagnosis code as shown in Figure 4.



Figure 4: Different care paths for different patient groups having same diagnosis

From figure 4, the largest number of patients is in diagnosis code 822 with 106 cases, followed by diagnosis code 106 with 90 cases, the rest being less than 8 cases each. Both diagnosis codes 822 and 106 split into more than 10 care paths each.

RQ3: Compliance with internal and external guidelines

Eventflow has sufficient capacity to present either group or individual cases with regard to time and activity sequence. It is for example possible to determine the time that a particular activity took place and the time between various activities in an individual case or same variant sequence by checking off the distribution options.

A number of decisions can be made just by checking if the patient actually entered process from the first activity or exited after the last activity as expected. Such information is revealed by pointing the cursor over the particular record and either taking it to the first of last activity which will be displayed on the control panel as shown in Figure 5.

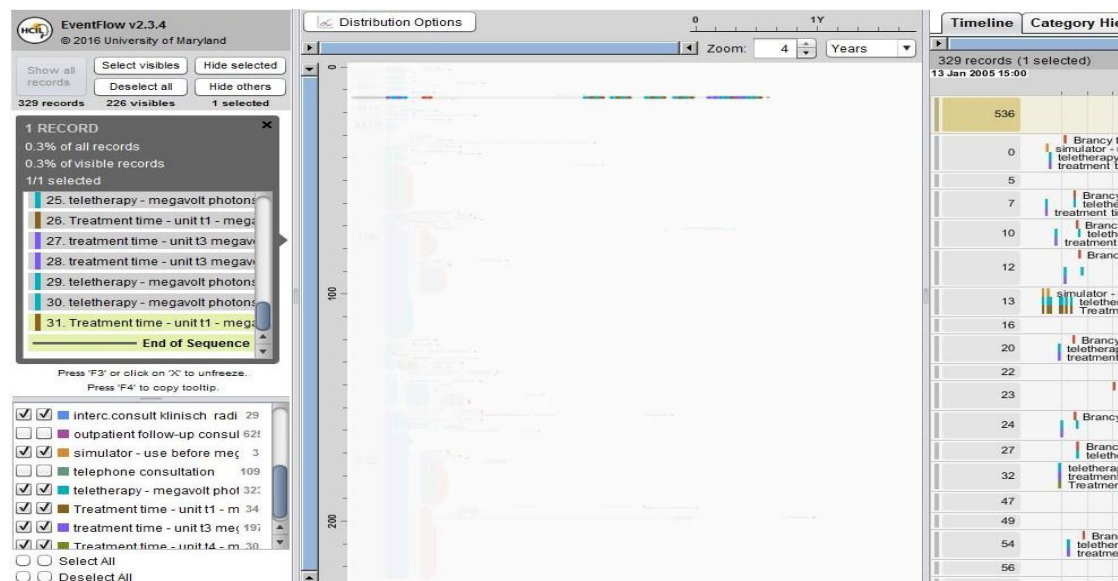


Figure 5: Last activity in a record sequence

The period between two adjacent or non-adjacent activities in a sequence can be revealed as shown in Figure 6.

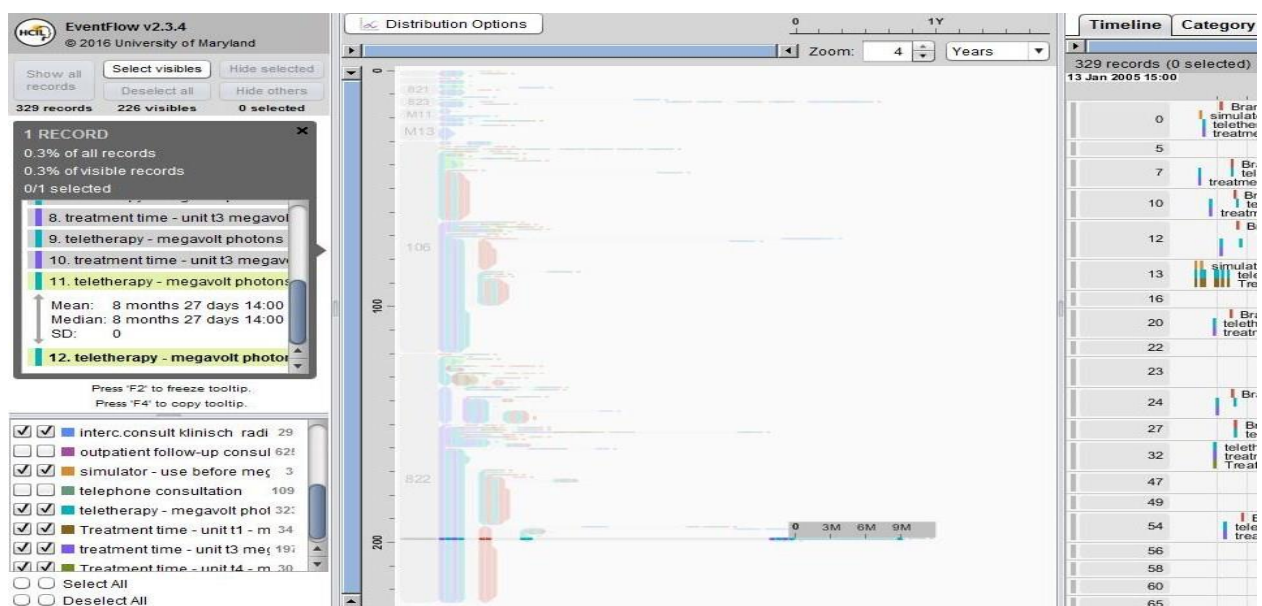


Figure 6: Period between two activities in a sequence.

The two treatment activities in question are highlighted in the overview panel and from the tooltip as in figure 7. The treatment activities teletherapy – megavolt photons bestrali and Branchy therapy – interstitial-intensei have a mean time of 1 month 5 days 20.54 hrs, a median of 1 month 4 days 16:00 hrs and SD of 3 days 21:12 hrs 40 s between them. The lengths of the individual activities are got from the control panel.

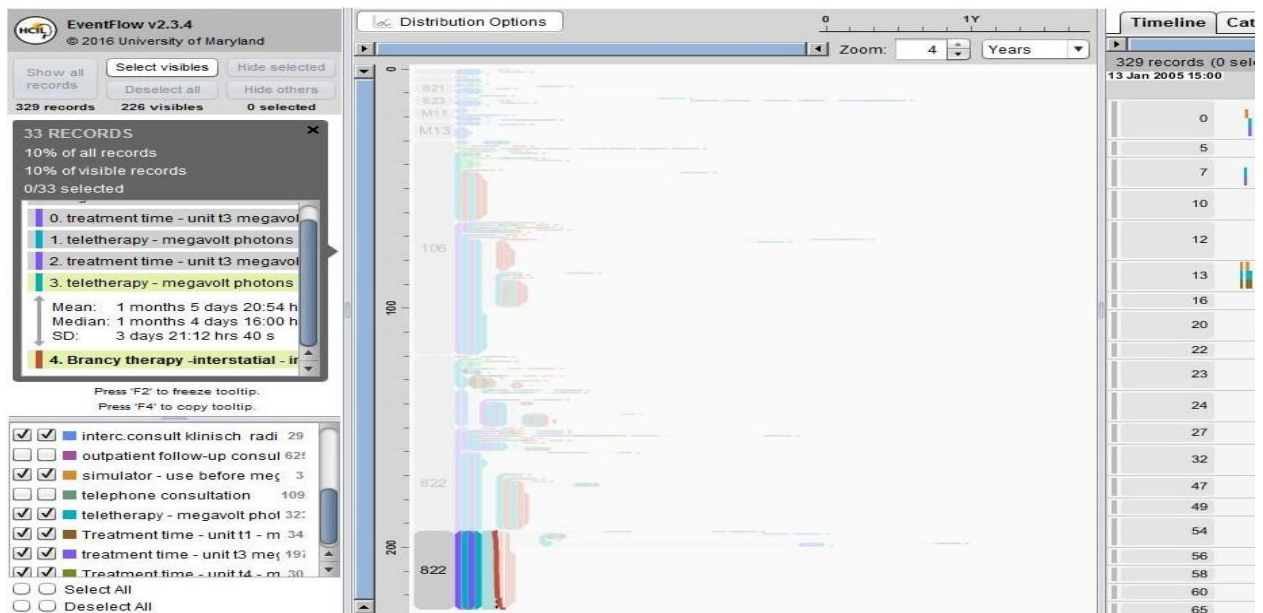


Figure 7: Distribution information between two activities in treatment

Discussion

Visual analytics overcomes the challenge of identification of the most common path/trace that is encountered in process mining. This is achieved by grouping all records with similar sequences together and by sorting; the most numerous common sequence placed is either at the top or bottom.

In addition to identification of the most common path/trace, more information on the event-log is available by pointing at the particular sequence and reading the information displayed on the control panel. It should be noted that cases that enter an activity (START) are often split, such that the ones that complete the activity (END) are different in number as regards a particular trace. For example in figure 2, Branchy therapy – interstitial – intense starts with 7.9% of all records but only 6.4% complete the process in the most common trace.

The earlier activities in a trace are part of a higher percentage of records since they are also part of other sequences such as: (1) 1st consultation outpatient (53.5% of all records), (2) treatment time unit t3 megavolt (28% of all records), (3) Teletherapy – megavolt photons bestrali: (25.2% of all records) and (4) Branchy therapy – interstitial – intense (7.9% of all records). The implication is that changes in the earlier activities of a most common trace have a higher impact compared to the later activities.

Exceptional paths that are depicted by very long sequence represent either very complex cases, or an indication of ineffective treatment that should be of concern to the health care facility. Such may indicate misdiagnosis, wrong prescription, resistance to drugs or a new disease.

A similar diagnosis, different care path, is not surprising since despite a common diagnosis, individual peculiarities of the patient determine the care path. However, the variation in care paths is expected to reflect some categorization such as age sets, and progression level of ailment (mild, intermediate, and severe). Such revelations can help management to restructure the section into subsections handling the different care paths if the numbers are significant such as in diagnosis code 822 and 106.

Questions pertaining to compliance to internal and external guidelines can be answered using visual analytics. Individual records can be inspected on aspects such as order of activities in a procedure, timing between activities, first and last activities. In comparison to process mining which treats all cases as part of a process model by eliminating those that do not fit, visual analytics accounts for each case and presents an easy way to audit all cases. The possibility of inspecting each patient record can be extended to resource performance.

Conclusion

Complexity and abstraction in healthcare data is a challenge when using process mining. Using an integrative approach, a number of previously open problems when using process mining can be solved using visual analytics. Three challenges in healthcare process mining including identification of most followed paths and exceptional paths; differences in care paths followed by different patient groups; and compliance with internal and external guidelines are solvable using visual analytics. The ability of visual analytics to reveal evidence hidden the data can be used by process owners even for operational running.

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